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Distributional impact of carbon pricing in Chinese provinces

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ABSTRACT

Based on a Multi-Regional Input-Output (MRIO) model, and combined with the 2012 MRIO table for 30 Chinese provinces, this paper analyzes the distributional impacts of carbon pricing on households within and across Chinese provinces. The results show regressive distributional effects of carbon pricing across provinces, i.e. poor provinces are affected more by the price. Carbon pricing also shows rural-urban regressivity (i.e. rural households are impacted more heavily than urban households) in more than half of the provinces. Within each selected province, carbon pricing has mostly regressive effects, i.e. poorer urban households are more affected than richer urban households in all provinces and poorer rural households more than richer rural households in one third of the provinces. When looking more specifically at direct energy consumption, we find that the carbon pricing on domestic fuels generally shows regressivity, while pricing carbon on transport fuels shows progressivity. In addition, the impact of carbon pricing on residential direct expenditures (mainly on electricity and coal) is the most important contributor to the regional regressivity across provinces.

1. Introduction

China has experienced fast economic growth with a rapid increase of energy consumption and CO_2 emissions over the past four decades (Feng et al., 2013). At the same time, its carbon intensity is still much larger than the carbon intensity of developed countries and the world average, due to large share of coal in China's energy mix (Minx et al., 2011). Moreover, when comparing per capita GDP across 31 provinces in 2017 (see Appendix Fig. A.1), China has significant income differences between provinces, in particular a big gap between coastal and inland provinces; in addition, China's urban-rural dual economic structure leads to pronounced inequality between rural and urban households. According to China Statistical Yearbook 2018 (NBS, 2018), in 2017, the average per capita disposable income of urban households was 36.4 thousand Yuan, while the average per capita disposable income of rural households was only about a third with 13.4 thousand Yuan. Moreover, the urban-rural gap shows significant differences across provinces. For example, in 2017, the per capita disposable income of Tianjin's urban residents was 1.85 times of its rural residents while the figure in Gansu was about 3.44 times.

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These issues constitute a complex situation with potentially contradictory goals for the Chinese government, which, on the one hand strives to maintain economic growth and mitigate the regional imbalance and income disparity, and on the other hand, attempts to realize energy conservation and emissions reduction to address climate change. To address climate change, the Chinese government has announced a series of emission reduction targets and declared the implementation of climate mitigation policies, such as carbon pricing to realize these targets. For example, China pledged to peak its CO_2 emissions around the year 2030 and potentially before that, and to reduce its carbon intensity by 60%–65% from the levels in 2005. To achieve its carbon pricing policy, China established seven pilot carbon markets in five cities and two provinces from 2013 to 2014, and launched the national carbon market for the power generation industry in December 19, 2017[1]; in addition, a carbon tax policy is also planned to come into effect as a complement to the carbon market after 2020.[2] Many economists and scholars support the implementation of the carbon tax in China due to its simplicity and transparency (Feng et al., 2010; Liang and Wei, 2012).

However, the implementation of carbon pricing may cause negative distributional effects. Due to differences in income and consumption patterns, different households groups would be impacted differently to the same stimuli. The concern that the carbon burden will fall more heavily on the poor is seen as a major obstacle to its policy acceptability because poor people often spend a larger share of income on energy-intensive products to meet their basic needs (e.g. heating, cooking, electricity) and lack options for substitution (Wang et al., 2016; Feng et al., 2018). Therefore, for China, which is experiencing its transition period and meanwhile facing the challenge of regional and urban-rural income disparities, distributional impact is a particularly important issue which affects social equity and justice. Assessing distributional impacts of carbon pricing in China can provide useful information for policy makers to help them better design the policy.

Carbon pricing attempts to internalize the external costs of carbon emissions into market prices and to provide an incentive to mitigate carbon emissions (Wang et al., 2016). There are two main types of carbon pricing: emissions trading systems (ETS) and carbon taxes (CT) (CPL, 2016). While numerous studies have focused on potential distributional issues of carbon pricing, most studies have focused on developed countries (Wang et al., 2016). Although several studies show that taxing carbon in certain developed countries/regions may be neutral (Symons et al., 2000; Creedy and Sleeman, 2006) or weakly progressive (Tiezzi, 2005; Oladosu and Rose, 2007; Sajeewani et al., 2015), more studies show that without carbon revenue recycling, a CT is regressive in most cases (Speck, 1999; Baranzini et al., 2000; Brännlund and Nordström, 2004; Wier et al., 2005; Kerkhof et al., 2008; Callan et al., 2009; Feng et al., 2010; Bureau, 2011; IPCC, 2014; Mathur and Morris, 2014). Regressivity means that the cost of a carbon tax to the income or welfare of lower income groups is higher than to the higher income groups, or in other words, the burden of carbon pricing on the poor is higher than on the rich. A potential regressive effect will aggravate inequality of a society (Feng et al., 2010; Büchs and Schnepf, 2013; Dennig et al., 2015). As for developing countries, there are much fewer studies, some of which show regressivity and some do not (Wang et al., 2016). Moreover, these studies show that the design on how the CT tax is implemented and how its revenue is recycled, could affect the distributional impact of CT (Zhang and Baranzini, 2004; Oladosu and Rose, 2007; Parry, 2015; Wang et al., 2016). Although research has paid less attention to the distributional effect of carbon emissions trading, they generally support the conclusion that ETS has a similar regressive effect as CT (Parry, 2004; Burtraw et al., 2009; Shammin and Bullard, 2009). For example, Burtraw et al. (2009) argued that through auctioning the emissions allowances and returning the auction revenues to households, the adverse distributional impact of ETS could be altered.

Overall, existing studies on carbon pricing mainly focus on the distributional effect within a country or a region, such as across income groups (Callan et al., 2009; Feng et al., 2010; Bureau, 2011; Mathur and Morris, 2014), between rural and urban households (Callan et al., 2009; Bureau, 2011; Pashardes et al., 2014), among households grouped by other demographic characteristics (e.g. family size (Wier et al., 2005; Callan et al., 2009) or households' socio-economic status (Feng et al., 2010)), but very few pay attention to the analysis from a multi-regional perspective.

As for China, there are several studies on the distributional impact of a hypothetical carbon price in China, e.g. on China's urban-rural gap (Liang and Wei, 2012); among different income groups (Brenner et al., 2007; Wang, 2009), or on a specific region such as Shanghai (Jiang and Shao, 2014). On the whole, studies paying attention to the distributional impact of carbon pricing between groups across different regions are lacking, which is the main contribution of this paper. This study aims to capture the details that a national-level or a single region analysis could not obtain, in order to put forward policy recommendations to policymakers on how to mitigate potential unintended adverse distributional effects of carbon pricing while maintaining the intended emission reduction effect. Given that both CT and ETS mechanisms ripple throughout the economic system by increasing the price of fossil fuels, these two carbon pricing polices share a number of similarities in terms of distributional effects, we believe that our analysis will hold for both carbon pricing instruments.

This study, therefore, focuses on analyzing the distributional impact of a certain carbon price on the households across different regions, through answering the following 3 research questions: (1) How will the carbon pricing impact regional inequality? (2) How will the carbon pricing impact rural and urban households within a region? (3) Will carbon pricing enlarge the inequality across income groups?

2. Materials and methods

Adopting similar approaches used by Wier et al. (2005), Kerkhof et al. (2008), Feng et al. (2010), we carry out analysis based on Multi-Regional Input-Output (MRIO) analysis to assess the impact of carbon pricing on households across China's 30 provinces. Fig. A.2 illustrates the research framework of this study.

2.1. Multi-regional input-output analysis

Multi-regional input-output (MRIO) analysis is a widely-used approach for analyzing the interactions among regions and sectors and thus can account for the carbon footprint of various economic agents (Liu et al., 2015). Therefore, the MRIO approach has been widely applied in energy & environment and ecological systems research, with a focus on topics such as carbon emission accounting and decomposition analysis of driving factors (Guan et al., 2008; Su et al., 2013; Liu et al., 2015; Fan et al., 2016), virtual water flows (Lenzen et al., 2013; Feng et al., 2014), land use (Weinzettel et al., 2013; Yu et al., 2013), toxins (Koh et al., 2016), and a wide range of other environmental and social indicators.

The MRIO model is an extension from the standard IO model to a larger economy that includes each industry in each country or region. The basic equation of the IO model is shown in Eq. 1

$$\mathbf{AX} + \mathbf{Y} = \mathbf{X} \tag{1}$$

where (in an n-sector economy):

[1] People's Daily Online. National Development and Reform Commission: China has officially launched the national carbon emissions trading system. 2017-12-19. Available from: http://finance.people.com.cn/n1/2017/1219/c1004-29716952.html.

[2] China Development. Is the carbon tax really coming? 2017-10-28. Available from: http://www.chinadevelopment.com.cn/news/ny/2016/10/1092535.shtml.

$\mathbf{X}$ ~ total output vector with n dimensions whose element X_i is the output of sector i;

$\mathbf{Y}$ ~ final demand vector with n dimensions whose element Y_i denotes final demand (including household and government consumption, investment, and exports) for goods i;

$\mathbf{A}$ ~ direct requirements matrix (or technology matrix) with n*n dimensions whose element a_{ij} represent the direct requirements of sector j on sector i per unit output of sector j.

For MRIO model, Eq. (1) could be rewritten as Eq. (2):

$$\begin{pmatrix} \mathbf{A}^{11} & \mathbf{A}^{12} & \cdots & \mathbf{A}^{1n} \\ \mathbf{A}^{21} & \mathbf{A}^{22} & \cdots & \mathbf{A}^{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{A}^{n1} & \mathbf{A}^{n2} & \cdots & \mathbf{A}^{nn} \end{pmatrix} \begin{pmatrix} \mathbf{X}^{1} \\ \mathbf{X}^{2} \\ \vdots \\ \mathbf{X}^{n} \end{pmatrix} + \sum_{v=1}^{n} \begin{pmatrix} \mathbf{Y}^{1v} \\ \mathbf{Y}^{2v} \\ \vdots \\ \mathbf{Y}^{nv} \end{pmatrix} = \begin{pmatrix} \mathbf{X}^{1} \\ \mathbf{X}^{2} \\ \vdots \\ \mathbf{X}^{n} \end{pmatrix} \tag{2}$$

where,

$\mathbf{A} = \begin{pmatrix} \mathbf{A}^{11} & \mathbf{A}^{12} & \cdots & \mathbf{A}^{1n} \\ \mathbf{A}^{21} & \mathbf{A}^{22} & \cdots & \mathbf{A}^{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{A}^{n1} & \mathbf{A}^{n2} & \cdots & \mathbf{A}^{nn} \end{pmatrix}$, whose submatrix $\mathbf{A}^{rn}$ is m by m matrix with each element $a_{ij}{}^{rn}$ representing the volume of commodity i in region r directly required to produce per unit output of sector j in region n; $i = 1, 2, \ldots, m$; $j = 1, 2, \ldots, m$;

$\mathbf{X} = \begin{pmatrix} \mathbf{X}^{1} \\ \mathbf{X}^{2} \\ \vdots \\ \mathbf{X}^{n} \end{pmatrix}$, whose submatrix $\mathbf{X}^{r}$ is a column vector with m dimensions; and its element $x_i{}^r$ representing the output of sector i in region r.

The submatrix $\mathbf{Y}^{rv}$ of the final demand vector $\begin{pmatrix} \mathbf{Y}^{1v} \\ \mathbf{Y}^{2v} \\ \vdots \\ \mathbf{Y}^{nv} \end{pmatrix}$ is a column vector with m dimensions whose element $y_i{}^{rv}$ denotes the sum of final demand of all items (including household and government consumption, investment, and exports)[3] for commodity i in region v from region r.

Eqs. (3) can be obtained from Eq. (2).

$$\mathbf{X} = (\mathbf{I} - \mathbf{A})^{-1} \cdot \mathbf{Y} = \mathbf{LY} \tag{3}$$

where,

$\mathbf{I}$ ~ m ∗ n dimension identity matrix;

$\mathbf{L} = (\mathbf{I} - \mathbf{A})^{-1}$ ~ m ∗ n dimension Leontief inverse matrix or total requirements matrix whose element $l_{ij}{}^{rn}$ represents the total volume of commodity i in region r required both directly and indirectly to produce one unit of final demand of commodity j in region n.

As shown in Eq. (4), total requirements matrix can be decomposed into three parts: $\mathbf{I}$, $\mathbf{A}$ and $\mathbf{A}^2 + \mathbf{A}^3 + \cdots + \mathbf{A}^n$. Of them, I denotes the unit final use produced by the m*n production sectors; A denotes the direct requirements matrix used by producing the unit final use; $\mathbf{A}^2 + \mathbf{A}^3 + \cdots + \mathbf{A}^n$ denotes the total indirect requirements matrix used by producing the unit final use. Therefore, Eq. (4) can comprehensively reflect the change in the total output of this sector and other sectors directly and indirectly induced by the change in the final demand of any sectors (Liang, 2007).

$$\mathbf{L} = (\mathbf{I} - \mathbf{A})^{-1} = \mathbf{I} + \mathbf{A} + \mathbf{A}^2 + \mathbf{A}^3 + \cdots + \mathbf{A}^n \cdots \tag{4}$$

2.2. Direct and indirect effects from pricing carbon

Through charging CO_2 emissions from fossil fuel combustion by households and industries, carbon pricing can reduce fossil fuel consumption and related emissions. The aim of this study is to measure and compare the impact of carbon pricing on households among different regions. Direct effects refer to charging direct emissions produced by households such as cooking, heating and driving; indirect effects refer to charging indirect emissions arising throughout the production steps required to produce households' final consumption items. Given that pricing carbon on fossil fuel consumption will lead to different prices of products, and different consumers have different consumption structures, the final tax burden may be unevenly distributed (Wang, 2009). Therefore, it is necessary to undertake a comparative analysis on the carbon pricing burden of different household groups between and within regions.

Consistent with existing studies (Wier et al., 2005; Kerkhof et al., 2008; Feng et al., 2010, 2018), this study also assumes that the carbon pricing burden imposed on production sectors can be fully passed onto the consumers, therefore, households bear both the direct and indirect impact by the carbon pricing. This approach ignores demand elasticities and substitution possibilities, which is a common shortcoming of these type of studies. The IO method can calculate the indirect emissions driven by final demand thus captures the indirect effect of carbon pricing. In this study, given our interest in impacts on households, we only focus on household consumption.

The total carbon payment of consumption category k is the sum of direct and indirect carbon payments.

$$CT_k = CT\_d_k + CT\_nd_k \tag{5}$$

where, CT_d_k, CT_nd_k and CT_k represent the direct, indirect, and total carbon (pricing) payment on consumption category k, respectively. When setting the carbon price as t Yuan/t CO_2, CT_k can be obtained through Eq. (6).

$$CT_k = (E\_d_k + E\_nd_k) \cdot t \tag{6}$$

where, E_d_k, E_nd_k denote the direct and indirect emissions due to the consumption on category k, respectively. Then production emissions coefficient C_k can be calculated by dividing the direct emissions of sector k by its total output.

Then, for the MRIO model, the indirect emissions coefficient matrix driven by final consumption is $\mathbf{CL}$, where $\mathbf{C} = \begin{pmatrix} \mathbf{C}^{11} & & & \\ & \mathbf{C}^{22} & & \\ & & \ddots & \\ & & & \mathbf{C}^{nn} \end{pmatrix}$, and submatrix $\mathbf{C}^{rr}$ is a m by m diagonal matrix whose element $C_{ii}{}^{rr}$ denotes the production emissions coefficient of sector i in region r. The indirect emissions vector driven by household h in region v can be obtained through Eq. (7):

$$\begin{pmatrix} \mathbf{E\_nd}_h{}^{1v} \\ \mathbf{E\_nd}_h{}^{2v} \\ \vdots \\ \mathbf{E\_nd}_h{}^{nv} \end{pmatrix} = \begin{pmatrix} \mathbf{C}^{11} & & & \\ & \mathbf{C}^{22} & & \\ & & \ddots & \\ & & & \mathbf{C}^{nn} \end{pmatrix} \cdot \begin{pmatrix} \mathbf{L}^{11} & \mathbf{L}^{12} & \cdots & \mathbf{L}^{1n} \\ \mathbf{L}^{21} & \mathbf{L}^{22} & \cdots & \mathbf{L}^{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{L}^{n1} & \mathbf{L}^{n2} & \cdots & \mathbf{L}^{nn} \end{pmatrix} \cdot \begin{pmatrix} \mathbf{Y}_h{}^{1v} \\ \mathbf{Y}_h{}^{2v} \\ \vdots \\ \mathbf{Y}_h{}^{nv} \end{pmatrix} \tag{7}$$

[3] Actually, when computing the result, this study disaggregate the final demand into household consumption, government consumption, investment, and exports; and the household consumption of each region can be further disaggregated into rural households and urban households consumption; moreover, the consumption expenditures of each rural households and urban households can be divided into different income brackets.

And the total indirect emissions driven by household h in region v can be obtained by Eq. (8):

$$E\_nd_h{}^v = \sum_{r=1}^{n} \sum_{i=1}^{m} E\_nd_{ih}{}^{rv} \tag{8}$$

2.3. Selection of indicators

To answer the three questions mentioned in the Introduction section, two types of indicators are selected in this study. One category is used to measure how heavy the carbon pricing burden is: 1) absolute value of per capita carbon payment, and 2) the per capita carbon payment burden rate. The per capita carbon payment is the average cost per person paid for his/her own carbon emissions. The per capita carbon pricing burden rate refers to per capita carbon payment as share of the per capita expenditure, which is the sum of the pre-tax per capita expenditure and the per capita total carbon payment. The second category indicates if the carbon pricing will exacerbate the regional imbalance. Here we choose the Suits index (Suits, 1977) to measure the distributional effect of carbon pricing.

The Suits index has been widely used to measure the distributional effect of a tax or public expenditure, including environmental taxes (Metcalf, 1999), vehicle pollution control policies (West, 2004), gasoline taxes (Agostini and Jiménez, 2015), and carbon taxes (Wier et al., 2005; Jiang and Shao, 2014). The index ranges from *+1*, i.e. extreme progressivity, where the entire tax burden is borne by members of the highest income bracket, through *0* for a proportional tax, to *−1*, which refers to extreme regressivity, at which the entire tax burden is borne by members of the lowest income bracket (Suits, 1977).

The calculation of Suits index is based on the idea of the Gini coefficient and the Lorenz curve (referred to as concentration curve by Suits). Fig. 1 shows an example of the concentration curve. The horizontal axis represents the accumulated percent of the income and the accumulated percent of the tax burden is plotted vertically. The population is ranked by income from low to high.

Following Suits (1977), the Suits index (S) can be calculated through Eq. (9):

$$S = (K - L)/K = 1 - (L/K) \tag{9}$$

where K is the area of the triangle OAB in Fig. 1, L is the area OABC between the curve and the horizontal axis OA. And L can be obtained through Eq. (10).

$$L = \int_0^1 T(r)dr \approx \sum_{i=1}^{n} (1/2)[T(r_i) + T(r_{i-1})](r_i - r_{i-1}) \tag{10}$$

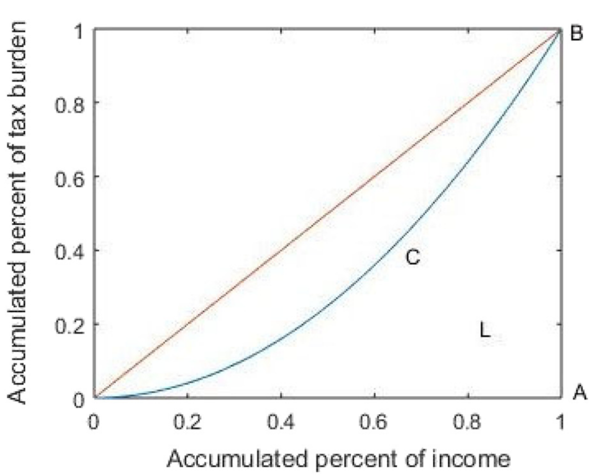

Fig. 1. The schematic diagram of the Suits index.

where r_i denotes the accumulated percent of income of the *ith* group, measured on the horizontal axis, which ranges from *0* to *1*; $T(r_i)$ is the corresponding accumulated percent of the tax burden borne by the ith group, and n stands for the number of households' income groups. For $r_0 = 0, T(r_0) = 0$, $K = 1/2$, the Suits index can be approximately obtained through Eq. (11).

$$S = 1 - 2L \approx 1 - \sum_{i=1}^{n} [T(r_i) + T(r_{i-1})](r_i - r_{i-1}) \tag{11}$$

2.4. Data source and data processing

The data source for this study is China's MRIO table for 2012 with 42 sectors in 30 provinces (excluding Tibet). Emissions data are taken from the China's provincial and national emissions inventory for 2012 provided by China Emission Accounts and Datasets (CEADs).[4] In this study, we only focus on CO_2 emissions associated with fossil fuels, thus the process emissions (e.g. emissions from cement production) are not included. Population data are taken from the China Statistical Yearbook 2013 (NBS, 2013).

2.4.1. Data processing for production emissions coefficients

CEADs emissions data includes 45 sectors while the sector number of MRIO is 42. Su et al. (2010) summarized two data treatment schemes to make the sector numbers between emissions coefficient and the Leontief inverse matrix compatible. The first is to aggregate the finer IO data to the level that matches the energy consumption data, while the other is to disaggregate the energy consumption data to the level that matches the IO data. We used both approaches to match the datasets and calculate production emissions intensity coefficients for 42 sectors in each of 30 provinces in China for the year 2012. The concordance matrix linking the datasets is shown in Appendix Table A.1.

2.4.2. Disaggregation of different income groups within provinces

In order to capture the differences of carbon pricing burdens between different household groups, we need to further disaggregate urban and rural households in 30 provinces of MRIO to the level of different income groups. The per capita annual consumption expenditure survey data for different urban and rural income groups in each province are taken from China provincial statistical yearbook 2013 for 30 provinces. The relationship between household consumption expenditure items and products of MRIO sectors is shown in Appendix Table A.2.

Since some provinces do not provide detailed data on households' expenditure at the level of income groups, we also illustrate the data availability in Fig. 2.[5] Specifically, the area marked by a star indicates that the data are available for both rural and urban income groups in that province; areas marked with a triangle denote that only the data on urban income groups are available; and the provinces with a cross represent that data are unavailable for both rural and urban income groups. In addition, there are also some regions, such as Tibet, Taiwan, Hong Kong and Macau, which are not discussed in this study due to data limitations. Finally, 12 provinces with a star label (Beijing, Heilongjiang, Shanghai, Zhejiang, Jiangsu, Henan, Jiangxi, Guangdong, Fujian, Guangxi, Chongqing, Gansu) are divided into different income groups within both rural and urban areas, while another 12 provinces marked with triangle (Tianjin, Jilin, Liaoning, Anhui, Hubei, Hainan, Sichuan, Inner Mongolia, Shaanxi, Qinghai, Ningxia, Xinjiang) are divided into different income groups only within the urban areas.

[4] China Emission Accounts and Datasets (CEADs): http://www.ceads.net/data/inventory-by-sectoral-approach/.

[5] Taking into account the possible similarity between neighboring provinces, we aggregate the 30 provinces in Fig. 2 to eight regions according to geographical characteristics.

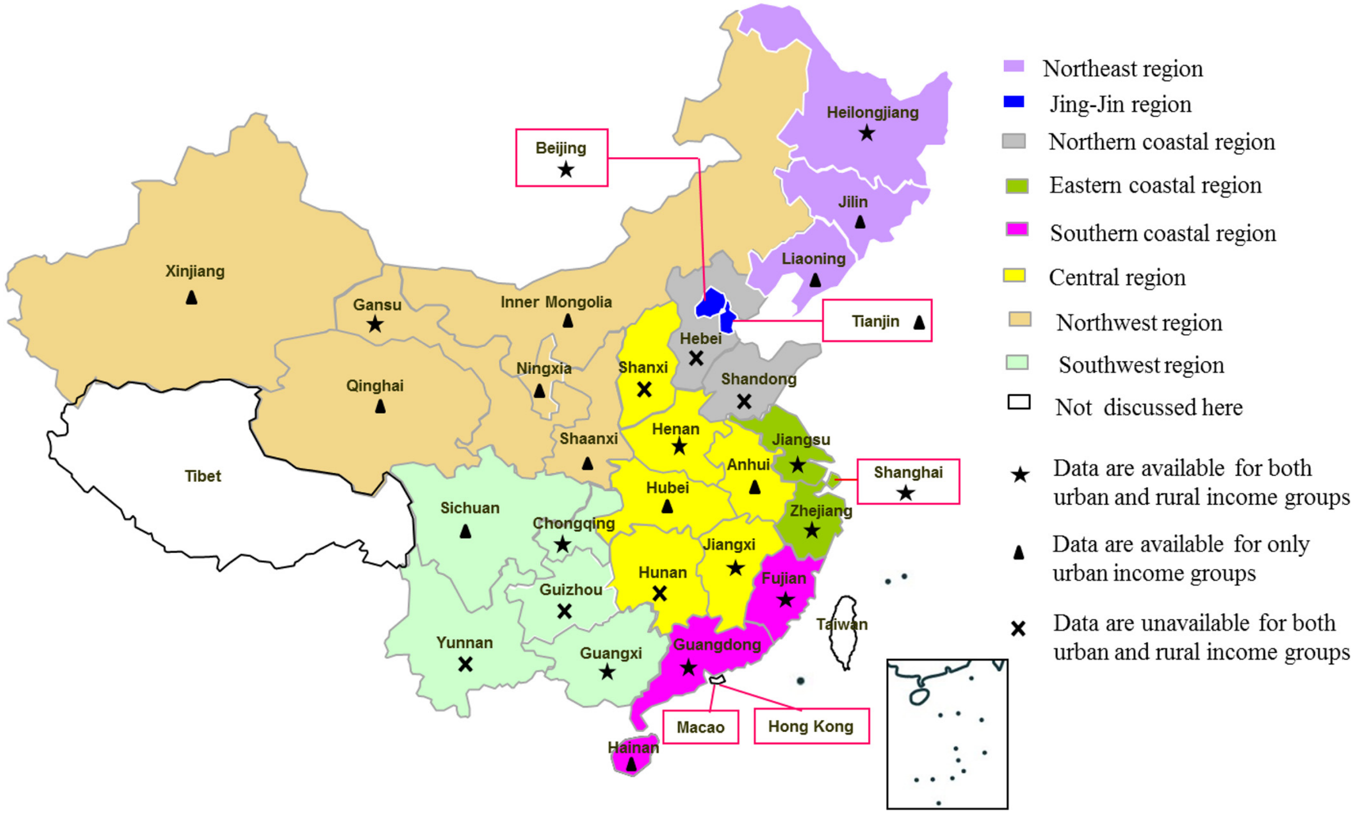

Fig. 2. Eight economic regions in mainland China.

2.5. Carbon pricing schemes

According to a preliminary estimate of the National Development and Reform Commission, in the long run, a carbon price of 300 Yuan/t CO_2 is regarded as a price which can play a role in leading the low-carbon green development.[6] From the experience of China's 7 pilot carbon markets, the average carbon price ranges from 10 to 50 Yuan/t CO_2.[7] Considering that a higher carbon price might lead to a heavier economic burden to industries and households, some studies suggest a lower rate ranging from 10 to 20 Yuan/t CO_2 (Su et al., 2011; Jiang and Shao, 2014). As a compromise (but not as a suggestion), we set the carbon price at 50 Yuan/t CO_2, and added a low carbon price scenario at 10 Yuan/t CO_2 and a high carbon price scenario at 100 Yuan/t CO_2 to construct a sensitivity analysis.

In this paper, all carbon pricing revenues are not recycled back to the economy, which also means that no social protection measures are considered.

2.6. Limitations

This study estimates the short-term distributional impacts of carbon pricing from an expenditure-side perspective, which means that the income changes of households due to the carbon pricing are not modeled; meanwhile, as mentioned in Feng et al. (2010), the behavioral response of consumers to higher prices and the associated changes in production are not considered within the current IO model framework. In fact, carbon pricing will affect household income through affecting the input of production factors and thereby the factor incomes such as wages and returns to capital (Feng et al., 2010; Liang and Wei, 2012; Liang et al., 2013). Meanwhile, in the long run, the production structure and production technology will change significantly, but these can be simulated only by more flexible models such as computable general equilibrium (CGE) models. However, production structures and consumption patterns can be rather rigid in the short run and thus the input-output approach provides a useful first approximation of short-run impacts and can put forward helpful information for policy makers on the fairness of carbon pricing mechanisms, and allows modeling and developing different measures to mitigate the regional regressivity of carbon pricing.

3. Results

3.1. Comparison of household's carbon burden for 30 provinces in China

If the implementation of a carbon pricing mechanism makes the less developed regions (with low per capita GDP) bear a higher carbon burden than more developed regions (with high per capita GDP), we define carbon pricing as regressive. Fig. 3 shows the carbon payment burden rate of residents in China's 30 provinces.

From Fig. 3 we can see that a carbon price of 50 Yuan/t CO_2 will bring an average per capita carbon payment burden rate of 0.67% to the households in China's 30 provinces, which is not heavy as a whole but shows significant differences across the provinces. Beijing would bear the lowest carbon burden rate (0.5%), followed by Fujian and Shanghai; while the three provinces with the highest burden rate are Inner Mongolia (1.38%), Qinghai (1.34%) and Heilongjiang (1.02%). The highly developed eastern areas, such as Beijing, Shanghai, Guangdong, Fujian and Zhejiang, generally bear a lower carbon burden; central regions like Henan, Hubei, Hunan and Anhui bear a burden rate which is close to the national average level, while the carbon burden rates of the economically underdeveloped areas, including the southwest and northwest regions, are relatively high. In other words, the carbon pricing is regressive across provinces.

[6] Economic Information Daily. The construction of the carbon market trading system enters the sprint period. 2017-10-30. Available from: http://www.jjckb.cn/2016-10/31/c_135792422.htm.

[7] China Carbon Emissions Trading Network. 2018-1-30. Available from: http://www.tanpaifang.com/.

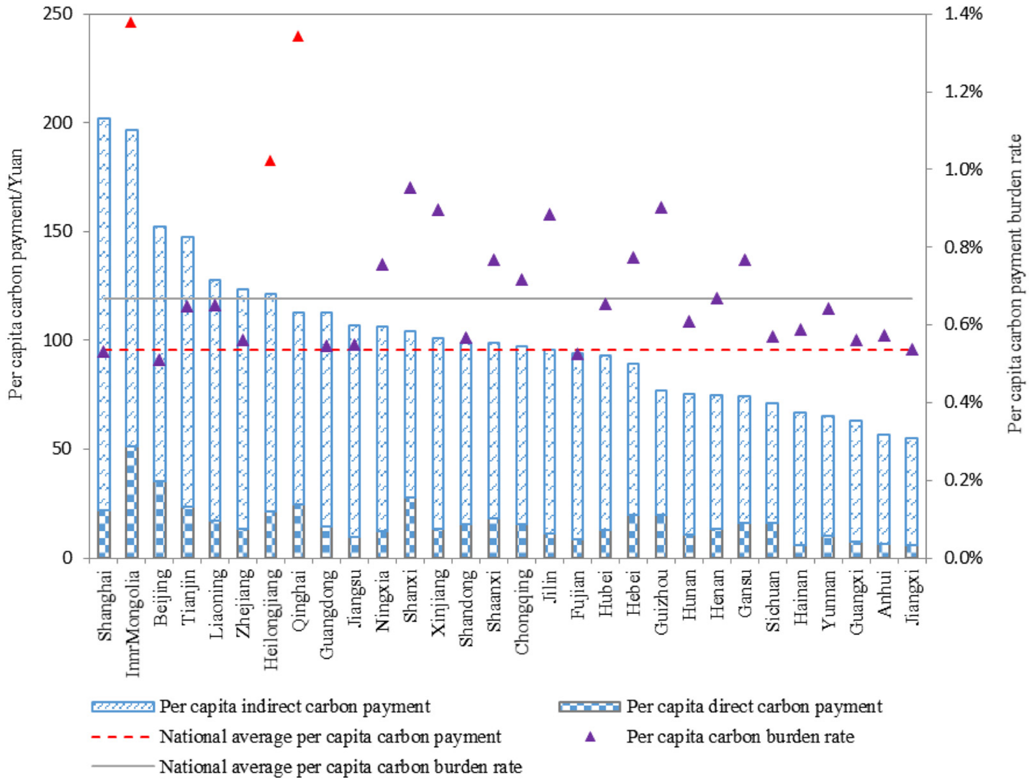

Fig. 3. Carbon burden rate among China's 30 provinces.

Per capita carbon burden rate is calculated by dividing the per capita carbon payments by per capita consumption expenditure. 30 provinces are ranked by per capita carbon payment from high to low on the horizontal axis.

Fig. 3 shows that the average per capita carbon payment is 95.8 Yuan. Generally, the per capita carbon payment in most provinces increases with per capita consumption with some noteworthy exceptions. For example, Qinghai has the lowest per capita expenditure, which is only 56% of the national average, but its per capita carbon payment is 17% higher than the national average. Inner Mongolia's per capita consumption is close to the national average, but its per capita carbon payment is 2.1 times the national average level, which is close to Shanghai's per capita carbon payment level. As a result, the carbon burden rate of these two provinces is significantly higher than that of other provinces. Shanghai's and Beijing's per capita carbon payments are relatively high with 2.1 and 1.6 times the national average level, respectively. But due to their higher per capita consumption level, which is 1.6 and 1 times higher than the national average, their per capita carbon burden rate becomes the lowest.

Fig. 3 also shows that the characteristics of indirect per capita carbon payments for China's provinces are similar to the total per capita carbon payment, and also plays a dominant role in the total per capita carbon payment. Their proportions range from 74% to 91%. Furthermore, direct per capita carbon payments are relatively stable across provinces and does not show a close correlation with per capita consumption levels. Therefore, compared with indirect per capita carbon payments, direct payments are more regressive.

We analyze the differences in the carbon burden rate between provinces through decomposing its structure as shown in Fig. 4, for 8 major categories of consumer goods. The top three contributors are Residence (which includes water, electricity, fuels and housing as shown in Table A.2), Transportation & Communication and Food, which account for about two-thirds of the total per capita carbon burden rate. In particular, for those provinces with a higher carbon burden, such as Inner Mongolia, Qinghai and Heilongjiang, Residence accounts for 51.4%, 64.9% and 48.6% carbon burden rate, respectively. However, for those with low carbon burden rates, such as Beijing, Fujian and Shanghai, the contribution of Residence to the total carbon burden rate is only 19.4%, 28.2% and 21.8%, respectively. Therefore, Residence is the most important contributor to the regional regressivity of carbon pricing. Moreover, by further analyzing the structure of Residence category, as shown in Fig. A.3, we find that electricity consumption plays a dominant role in most provinces, followed by coal and gas consumption.

3.2. Distribution of carbon burdens between rural and urban households within each province

There is a large income gap between China's urban and rural residents. In general, the income and expenditure level of urban residents is larger than that of rural residents. If the implementation of carbon pricing mechanism will make rural residents bear a higher carbon burden than urban residents, the carbon pricing is regressive, which can be called rural-urban regressive here, and vice versa. Similarly, if carbon pricing makes the lower income groups shoulder heavier than the higher income groups, the carbon pricing is regressive across income groups.

We calculated the per capita direct, indirect and total carbon burden for both urban and rural households in each of the 30 provinces. The per capita total carbon burden rate is the sum of per capita direct carbon burden rate and per capita indirect carbon burden rate. To highlight the rural-urban differences, we further calculate the relative gap in carbon burden between urban and rural households in each province, as shown in Fig. 5.

Fig. 5a shows the rural-urban relative gap caused by the total carbon pricing. We can see that the carbon pricing are rural-urban regressive in more than half of the 30 provinces whereas a handful of provinces show relatively weak rural-urban progressivity.

The direct carbon pricing causes rural-urban regressivity to 23 of the 30 provinces (see Fig. 5b). And the regressivity is much stronger than

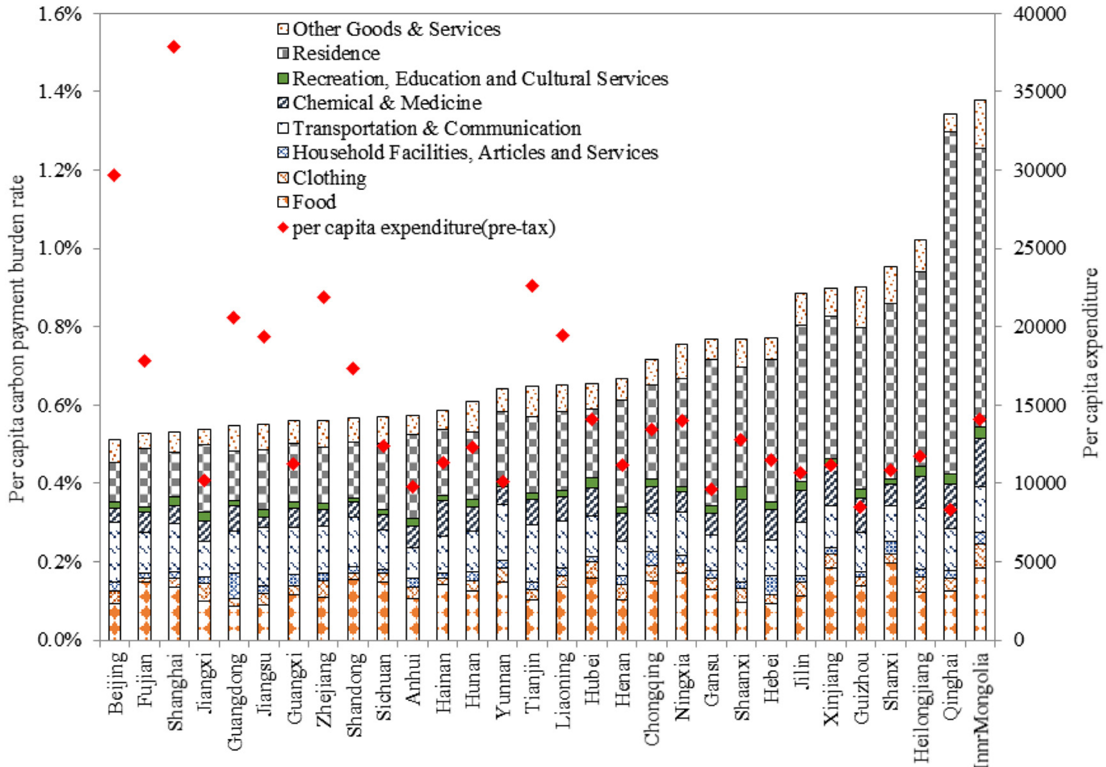

Fig. 4. Per capita carbon payment burden rate by consumption categories of goods and services.

that of the total carbon pricing and the indirect carbon pricing. Through analyzing the three components of direct carbon pricing (coal, petroleum and gas), we find that the carbon payment due to coal consumption show obvious rural-urban regressivity in almost all provinces, which is the main reason for the strong rural-urban regressivity of the direct carbon pricing. Unlike direct carbon pricing, as shown in Fig. 5c, the indirect carbon payment brings relatively weak rural-urban progressivity to 20 provinces while causes rural-urban regressivity to the remaining 10 provinces.

3.3. Inequality of the carbon tax payment

This section chooses the Suits index (see Eq. (11)) to measure the distributional effects of carbon pricing, in order to accurately reflect whether the carbon pricing will exacerbate China's regional imbalance and how serious it is. Table 1 shows the Suits index of carbon pricing in rural, urban and total households among 30 provinces. We calculate the Suits index to represent the direct, indirect and total distributional effects of carbon pricing, respectively.

As shown in Table 1, pricing carbon on fossil energy consumption at a price of 50 Yuan/t CO_2 will have a regressive distributional effect to rural, urban and national total households across 30 provinces. Among them, the direct carbon payment, namely, the payment due to households' direct carbon emissions, has a stronger regressive effect in the rural, urban and the total households, with the regressivity in the national total being the strongest. The indirect carbon payment, which can be understood as the cost of carbon pricing transferred from the production sectors, shows a relatively weak regressivity.

Overall, direct carbon pricing has the most obvious regressivity, while indirect carbon pricing has a relatively weak regressivity, and in total, carbon pricing has weak regressivity. Moreover, the extent of regressivity for urban is somewhat stronger than for rural households, and the regressivity within the national total households is between the extent for rural and urban, with an exception that the national Suits index of the direct carbon payment shows the most significant regressivity.

3.4. Comparison of carbon burdens among different income groups within each province

This section wants to further explore whether the carbon pricing will have an uneven distributional effect among different income groups within each province. As mentioned in Section 2.4, due to data limitation, only 12 provinces are divided into different income groups within both rural and urban areas, while another 12 provinces are disaggregated only within the urban (see Fig. 2).

And Fig. 6 presents the carbon burden rate of different income groups within these provinces.

Fig. 6 shows that, overall, the distributional effect of uniform national carbon pricing within urban areas in most provinces (and also within a few provinces' rural areas) would exacerbate income disparity in these areas. But, some areas show progressive distributional effects in that carbon pricing burden increases with the income level, such as rural Shanghai, Fujian and Guangxi, and urban Hainan and Sichuan, as well as urban and rural Jiangxi. Finally, although the carbon burden rate of a national uniform carbon price is distributed unevenly across different income groups in each area, this difference is relatively small compared with the gap between provinces or the gap between rural and urban households in each province.

In order to obtain an accurate distributional effect of carbon pricing, we calculate the Suits index in each region, as shown in Table A.3. Fig. 2 classifies the observed 24 provinces into 7 regions, thus Table A.3 can provide results about distributional impacts of carbon pricing from both provincial and regional levels.

For most provinces, carbon pricing has regressive distributional effects both across different urban-rural income groups (see overall Suits index) and within urban groups themselves. While, it shows

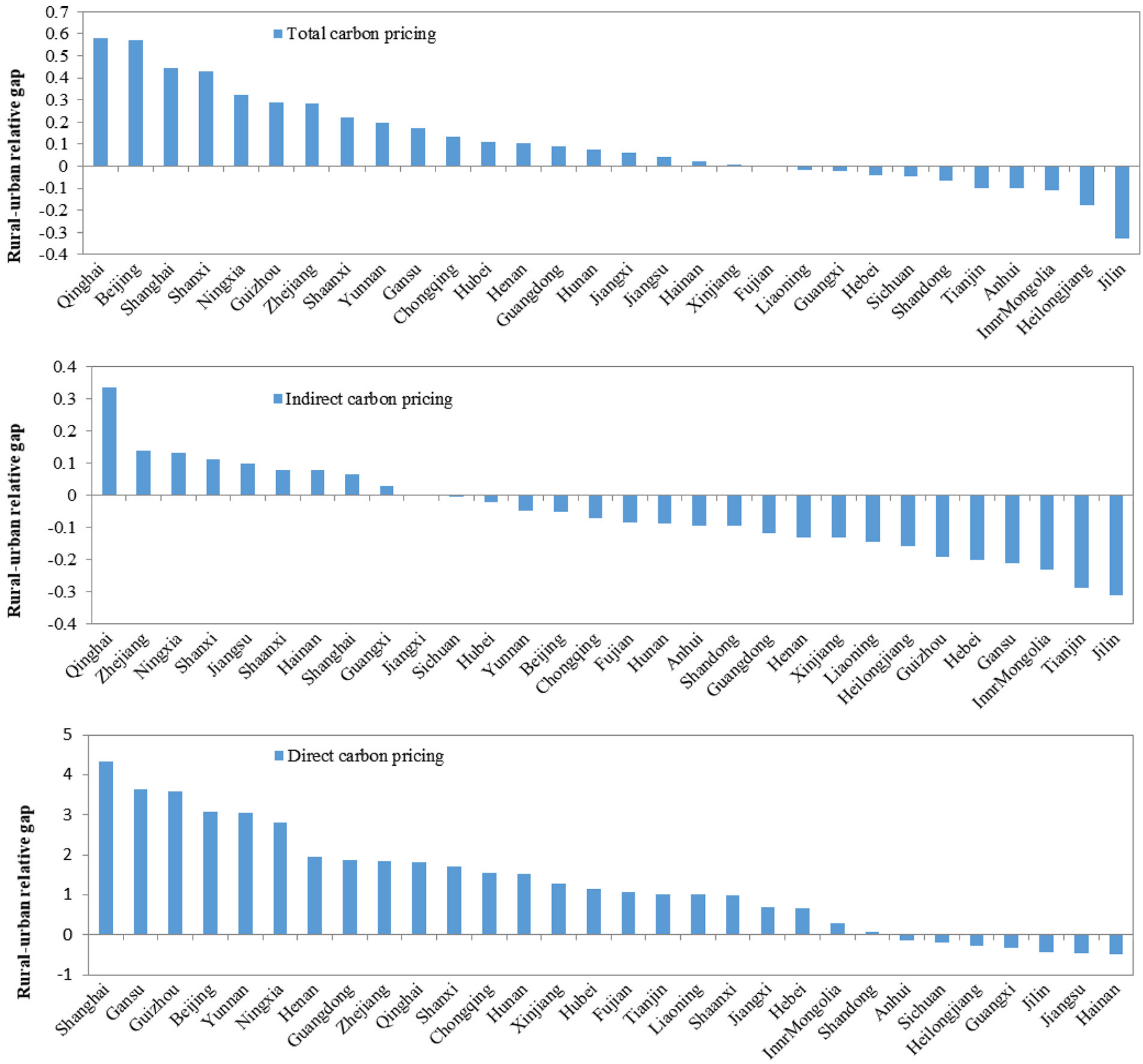

Fig. 5. Rural-urban gap in the carbon burden rate in each of 30 provinces. (a) Total carbon pricing; (b) direct carbon pricing; (c) indirect carbon pricing. (Notes: The rural-urban relative gap is obtained through dividing the per capita burden rate of rural households by that of urban households and minus one, thus a positive value means that the carbon pricing is rural-urban regressive.)

weak progressivity in two-thirds of the 12 selected rural areas. In addition, direct carbon payments show much stronger regressivity than indirect carbon payments, as a result, total carbon payments shows less regressivity in most provinces.

We further categorize direct energy consumption into domestic fuels (coal and gas) and transport fuels (petroleum) according to the purpose of energy use, and calculate the Suits index of carbon pricing on domestic fuels and on transportation fuels, respectively, as shown in the first two columns of Table A.3. The carbon payment due to domestic fuels shows regressivity, while the carbon payment on transport fuels shows progressivity, independent of urban-rural status.

Table 1
the Suits index of carbon pricing.

Suits index	Direct carbon payment	Indirect carbon payment	Total carbon payment
Rural	−0.130	−0.024	−0.049
Urban	−0.132	−0.066	−0.075
National total	−0.210	−0.032	−0.060

Note: The national total here only contains the 30 provinces observed in this study.

3.5. Sensitivity analysis

In this section, sensitivity analyses are performed by setting the carbon price at 10 and 100 Yuan/t CO_2, respectively. As shown in Fig. 7, the average per capita carbon burden rate caused by carbon prices of 10, 50 and 100 Yuan/t CO_2 are 0.134%, 0.667% and 1.324%, respectively. Since the carbon payment under the carbon prices 10–100 are all much lower than the level of the pre-tax per capita expenditure, the obtained carbon burden rate almost shows proportional increase with the prices ranging from 10 to 100 Yuan/t CO_2. In addition, we also find that the ranking of 30 provinces by the per capita carbon burden rate does not change with the increase of the carbon price.

Furthermore, we also compare the rural-urban distributional effects under different carbon prices (10 and 100 yuan) and calculate their corresponding Suits index. Results show that no directional changes occur

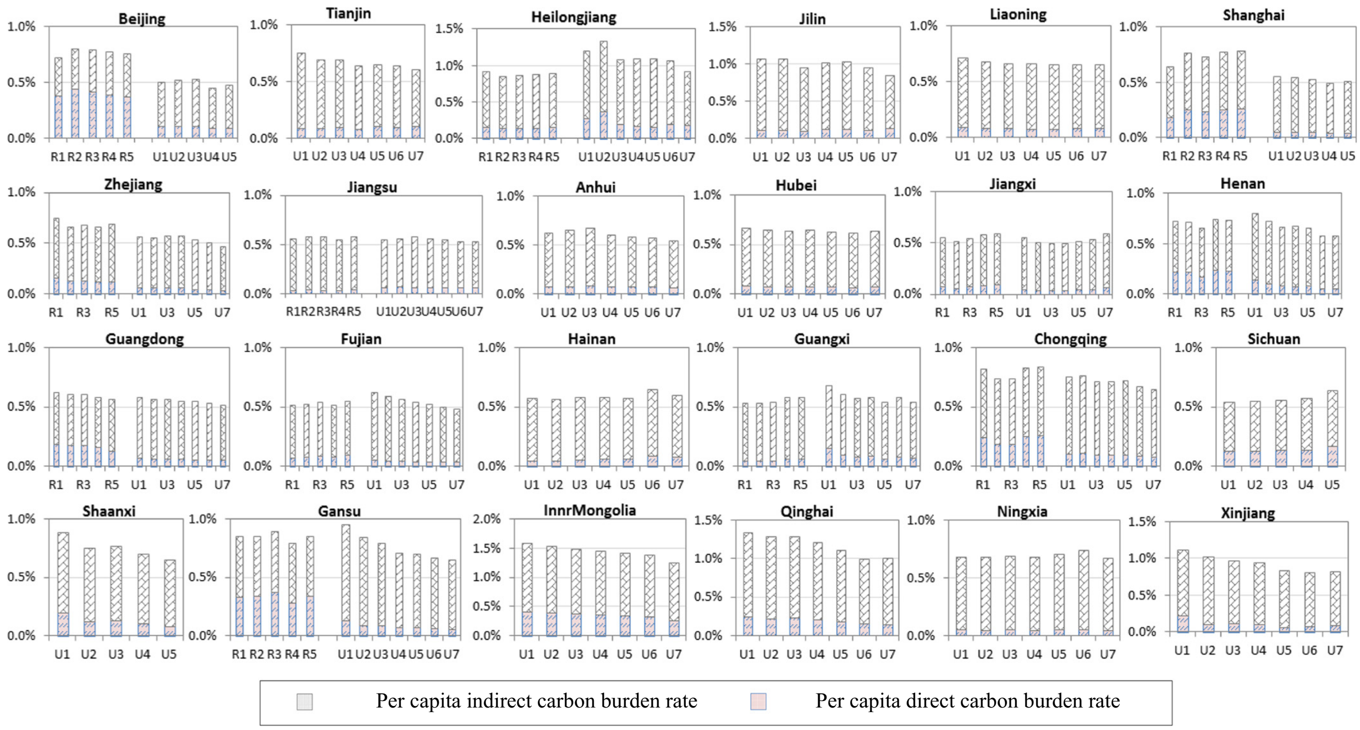

Fig. 6. Per capita carbon burden rate of different income groups in each province. (Notes: R1, R2, R3, R4, R5 denote different income groups of rural households from low income level to high; U1, U2, U3, U4, U5, U6, U7 represent different income groups of urban households from low income level to high.)

in distributional impacts independent of province and income group. Moreover, the absolute value of the Suits index will decrease very slightly with an increase of the carbon price. This result is directly related to our assumption that consumer behavior does not change immediately after the introduction of the carbon pricing policy. This hypothesis is strong in the long term, but it is acceptable in assessing the potential short-term impact of carbon pricing.

4. Conclusions and policy implications

This study employed the MRIO model to analyze the regional distributional impact of a national uniform carbon price in China. Based on our results we can draw several conclusions:

First, carbon pricing effects are different across provinces. The average carbon burden rate caused by a carbon price of 50 Yuan/t CO_2 is

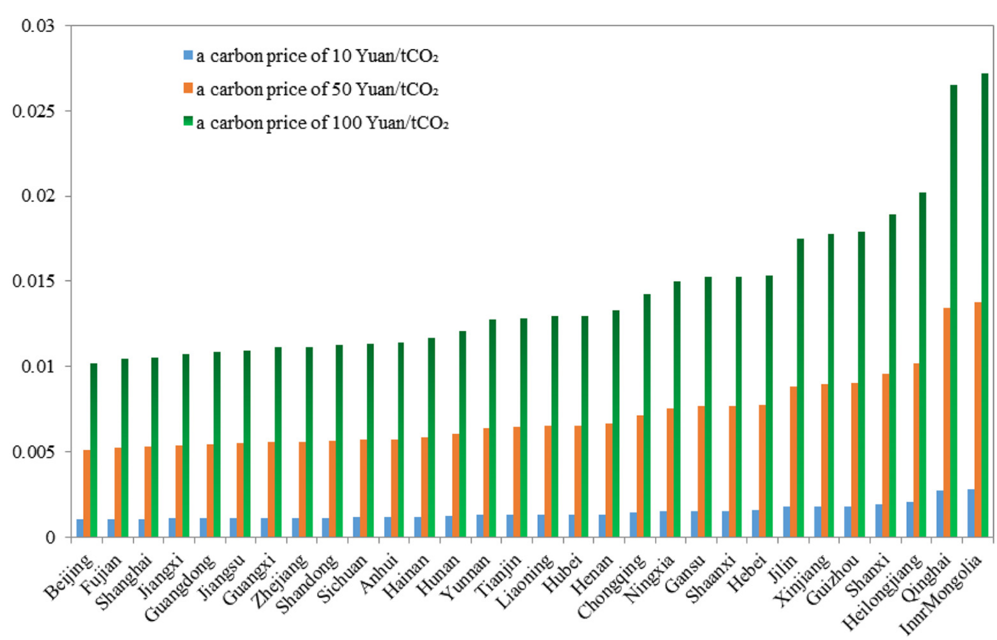

Fig. 7. Provincial carbon burden rates for different carbon prices.

0.67%, which is not heavy as a whole but is unevenly distributed across provinces. Richer provinces such as Beijing, Shanghai and Guangdong bear a lower carbon pricing burden than the poorer provinces in Western China. Meanwhile, the residence category contributes most to the regressivity of carbon pricing, and electricity and coal constitute the main parts to direct household expenditure for heating and cooling and similar items. This emphasizes the need to put high importance on the optimization of the energy and electricity structure, and to a reduction of coal use, especially by households.

Second, carbon pricing shows rural-urban regressivity in more than half of the 30 provinces, which indicates that a national uniform carbon price would widen the rural-urban gap in these provinces. In other provinces, the carbon pricing show weak rural-urban progressivity or approximately proportional distributional effect between rural and urban. This shows that rural households (especially rural low income groups which are lacking political influence polit) are the most vulnerable groups to the potential negative impact of carbon pricing, and thus need to be paid special attention to.

Third, the direct effect of carbon prices shows a relatively strong regressivity for all household categories and provinces, while the indirect effects show relatively weak regressivity. In total, the carbon pricing has weak regressivity for all household types and provinces.

Fourth, carbon pricing has regressive distributional effects across different income groups within urban households of most provinces; while for rural income groups, it is weakly progressive in two-thirds of the 12 selected rural areas. In addition, the distributional impact of direct carbon payments is regressive in most provinces, and the extent of such regressivity is stronger than that of indirect carbon payments and total carbon payments.

Finally, when categorizing the direct energy consumption into domestic fuels (coal and gas) and transport fuels (petroleum), in general, the carbon pricing on domestic fuels shows regressivity, while pricing carbon on transport fuels shows progressivity, for all households and provinces. This result reminds policymakers that different carbon pricing policies should be designed between domestic fuels and transport fuels. Households are very small emission sources, which are not included in the carbon market system at present. Once a carbon tax is considered for all emission sources that are not covered by the carbon market, we recommend households' transportation fuels rather than domestic fuels could be taxed first. If domestic fuels are also to be taxed for households, extra measures for vulnerable low income groups should be taken to avoid its potential regressive effects.

Results of this study show that carbon pricing may increase the rural-urban gap, the provincial gap and the inequality within provinces, but overall, such a regressive distributional impact is not strong. From the experience of China's 7 carbon market pilots, we can see that the overall current carbon price is still at a rather low level ranges from 10 to 50 Yuan/t CO_2, which has not created an onerous impact on economy and living standards. However, with higher future carbon prices, the burden caused might create social hardship for lower income groups and rural households.

Given that the current regional imbalance and income disparity have already been very large, adequate attention should be paid to even a small regressive policy. Based on our results, we suggest that when China gradually establishes more comprehensive carbon markets and higher prices, measures need to be taken to mitigate potential regressive distributional impacts. For example, the most practical way might be recycling the carbon pricing revenues to vulnerable/low-income households of the most affected areas.

Acknowledgements

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Appendix A

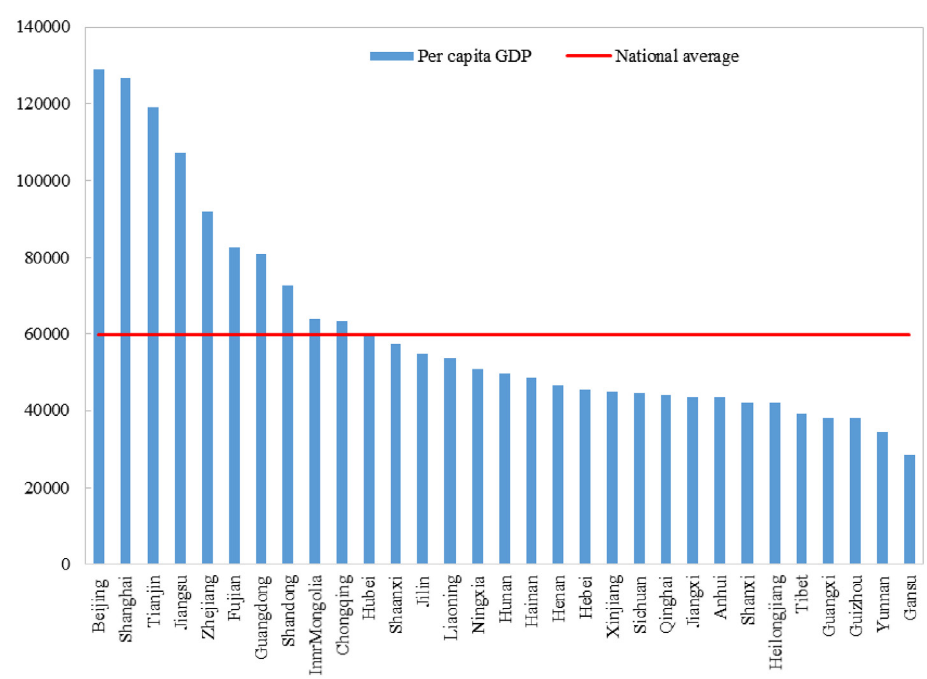

Fig. A.1. Per capita GDP of 31 provinces in China for 2017.
(Data source: China Statistical Yearbook 2018 (NBS, 2018).)

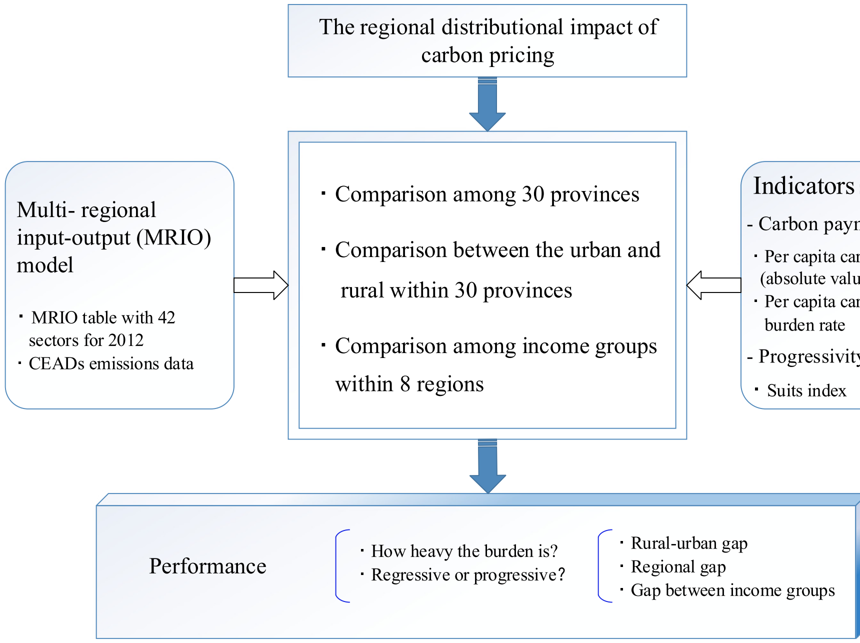

Fig. A.2. Research framework.

Table A.1
The relationship between the sectors of provincial-level CO_2 emission inventory from CEADs and the sectors of MRIO table.

Sectors of provincial-level CO_2 emission inventory from CEADs		Sectors of MRIO table	
Code	Sector name	Sector name	Code
1	Farming, Forestry, Animal Husbandry, Fishery and Water Conservancy	Farming, Forestry, Animal Husbandry, Fishery Products and Services	1
8	Logging and Transport of Wood and Bamboo		
2	Coal Mining and Dressing	Coal Mining and Dressing Products	2
3	Petroleum and Natural Gas Extraction	Petroleum and Natural Gas Extraction Products	3
4	Ferrous Metals Mining and Dressing	Metals Mining and Dressing Products	4
5	Nonferrous Metals Mining and Dressing		
6	Nonmetal Minerals Mining and Dressing	Nonmetal Minerals and Other Minerals Mining and Dressing Products	5
7	Other Minerals Mining and Dressing		
9	Food Processing	Food and Tobacco	6
10	Food Production		
11	Beverage Production		
12	Tobacco Processing		
13	Textile Industry	Textile	7
14	Garments and Other Fiber Products	Garments and Other Fiber Products	8
15	Leather, Furs, Down and Related Products	Leather, Furs, Down and Related Products	
16	Timber Processing, Bamboo, Cane, Palm Fiber & Straw Products	Wood Processing products and Furniture	9
17	Furniture Manufacturing		
18	Papermaking and Paper Products	Papermaking, Printing, Cultural, Educational and Sports Articles	10
19	Printing and Record Medium Reproduction		
20	Cultural, Educational and Sports Articles		
21	Petroleum Processing and Coking	Petroleum Processing and Coking Products	11
22	Raw Chemical Materials and Chemical Products	Chemical Products	12
23	Medical and Pharmaceutical Products		
24	Chemical Fiber		
25	Rubber Products		
26	Plastic Products		
27	Nonmetal Mineral Products	Nonmetal Mineral Products	13
28	Smelting and Pressing of Ferrous Metals	Smelting and Pressing of Metals	14
29	Smelting and Pressing of Nonferrous Metals		
30	Metal Products	Metal Products	15
31	Ordinary Machinery	Ordinary Machinery	16
32	Equipment for Special Purposes	Equipment for Special Purposes	17
33	Transportation Equipment	Transportation Equipment	18
34	Electric Equipment and Machinery	Electric Equipment and Machinery	19
35	Electronic and Telecommunications Equipment	Electronic and Telecommunications Equipment	20
36	Instruments, Meters, Cultural and Office Machinery	Instruments, Meters, Cultural and Office Machinery	21
37	Other Manufacturing Industry	Other Manufacturing Industry; Services for Metal Products, Machinery and Equipment	22, 24
38	Scrap and Waste	Scrap and Waste	23

(continued on next page)

Table A.1 (*continued*)

Sectors of provincial-level CO_2 emission inventory from CEADs		Sectors of MRIO table	
Code	Sector name	Sector name	Code
39	Production and Supply of Electric Power, Steam and Hot Water	Production and Supply of Electric Power, Steam and Hot Water	25
40	Production and Supply of Gas	Production and Supply of Gas	26
41	Production and Supply of Tap Water	Production and Supply of Tap Water	27
42	Construction	Construction	28
43	Transportation, Storage, Post and Telecommunication Services	Transportation, Storage and Post	30
44	Wholesale, Retail Trade and Catering Services	Wholesale, Retail Trade	29
		Accommodation and Catering Services	31
45	Others	Information Transmission, Software and Information Technology Services	32
		Finance	33
		Real Estate	34
		Leasing and Commercial Services	35
		Scientific Research and Technical Services	36
		Water Conservancy, Environment and Public Facilities Management	37
		Resident Services, Repairs and Other Services	38
		Education	39
		Health and Social Work	40
		Culture, Sports and Entertainment	41
		Public Management, Social security and Social Organizations	42

Table A.2
The relationship between household consumption expenditure items and the sectors of MRIO table.

Expenditure items	Sectors of MRIO table
Food	1, 6
Clothing	7–8
Household Facilities, Articles and Services	9, 15–17, 19, 21
Transportation & Communication and Food	11, 18, 20, 30, 32
Chemical & Medicine	12, 40
Recreation, Education and Cultural Services	10, 39, 41
Residence	2, 13, 25–28, 34–35
Water, electricity and fuels	2, 25–28,
Housing	13, 34–35
Other Goods & Services	22, 24, 29, 33, 36–38, 42
Accommodation and Catering Services	31

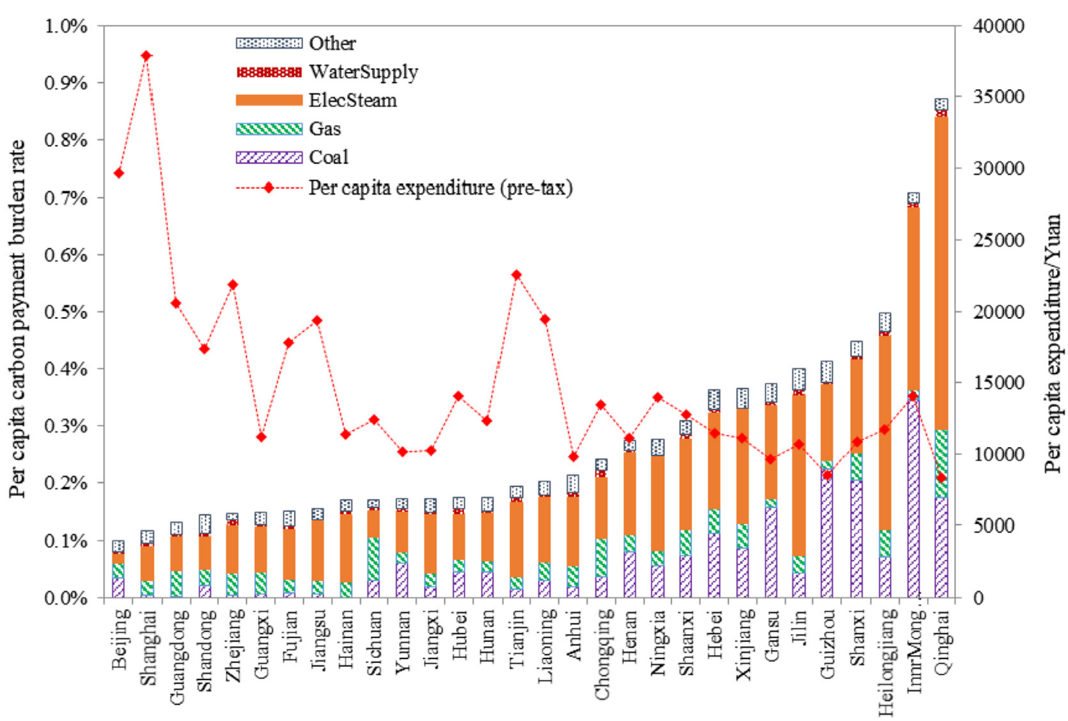

Fig. A.3. Structure of carbon burden rate on residence category by 30 provinces.

Table A.3
Suits index of carbon pricing.

Regions	Provinces	Suits index	Energy domain		Direct carbon payment	Indirect carbon payment	Total carbon payment
			Transport fuels	Domestic fuels			
Jing-Jin (JJ)	Beijing	Rural	0.0982	−0.0297	−0.0209	0.0260	0.0019
		Urban	0.0640	−0.2504	−0.0409	−0.0158	−0.0208
		Overall	0.0985	−0.5033	−0.1909	−0.0101	−0.0523
	Tianjin	Urban	0.0911	−0.1695	0.0345	−0.0392	−0.0286
Northeast (NE)	Heilongjiang	Rural	0.0556	−0.0202	0.0117	−0.0020	0.0002
		Urban	0.2759	−0.3384	−0.0875	−0.0363	−0.0455
		Overall	0.2222	−0.1556	−0.0003	0.0078	0.0063
	Jilin	Urban	0.2493	−0.1197	0.0428	−0.0436	−0.0333
	Liaoning	Urban	0.3109	−0.1276	0.0106	−0.0109	−0.0085
Eastern Coastal (EC)	Shanghai	Rural	0.0526	0.0415	0.0470	0.0134	0.0244
		Urban	0.0062	−0.1661	−0.0567	−0.0151	−0.0188
		Overall	−0.1414	−0.3429	−0.2233	−0.0171	−0.0407
	Zhejiang	Rural	0.0704	−0.1087	−0.0385	0.0023	−0.0052
		Urban	0.0691	−0.2720	−0.1502	−0.0279	−0.0381
		Overall	−0.1459	−0.3300	−0.2614	−0.0359	−0.0607
	Jiangsu	Rural	0.0435	−0.0068	0.0258	−0.0024	−0.0010
		Urban	0.0430	−0.1460	−0.0200	−0.0154	−0.0158
		Overall	0.1026	−0.0612	0.0475	−0.0217	−0.0157
Central Region (CR)	Henan	Rural	0.0872	0.0143	0.0214	0.0023	0.0080
		Urban	0.1582	−0.2281	−0.1345	−0.0354	−0.0465
		Overall	0.0426	−0.3534	−0.2911	0.0114	−0.0421
	Jiangxi	Rural	0.1052	0.0596	0.0740	0.0151	0.0232
		Urban	0.3144	−0.0216	0.1067	0.0185	0.0261
		Overall	0.0851	−0.1384	−0.0598	0.0098	0.0026
	Anhui	Urban	0.2011	−0.1369	−0.0339	−0.0371	−0.0367
	Hubei	Urban	0.1949	−0.1181	−0.0150	−0.0070	−0.0079
Southern Coastal (EC)	Guangdong	Rural	0.0129	−0.1431	−0.0776	0.0027	−0.0191
		Urban	0.1035	−0.1494	−0.0498	−0.0145	−0.0181
		Overall	−0.1223	−0.2632	−0.2065	0.0027	−0.0243
	Fujian	Rural	0.0621	0.0374	0.0465	0.0034	0.0098
		Urban	0.1088	−0.1988	−0.0537	−0.0374	−0.0386
		Overall	−0.0096	−0.2517	−0.1476	−0.0118	−0.0243
	Hainan	Urban	0.1692	−0.0006	0.0933	0.0046	0.0137
Southwest (SW)	Guangxi	Rural	0.0755	0.0948	0.0827	0.0155	0.0215
		Urban	0.2095	−0.2414	−0.0755	−0.0122	−0.0206
		Overall	0.0892	−0.0125	0.0307	−0.0107	−0.0057
	Chongqing	Rural	0.0666	0.0388	0.0436	0.0048	0.0158
		Urban	0.0749	−0.0940	−0.0614	−0.0204	−0.0256
		Overall	−0.1178	−0.2358	−0.2139	−0.0020	−0.0361
	Sichuan	Urban	0.3035	0.0061	0.0651	0.0299	0.0382
Northwest (NW)	Gansu	Rural	0.0248	−0.0081	−0.0078	−0.0019	−0.0042
		Urban	0.0872	−0.1329	−0.1141	−0.0459	−0.0527
		Overall	0.1698	−0.3482	−0.3326	0.0166	−0.0588
	Shaanxi	Urban	0.1199	−0.2565	−0.1576	−0.0318	−0.0516
	Inner Mongolia	Urban	0.0682	−0.0778	−0.0742	−0.0245	−0.0362
	Qinghai	Urban	0.1423	−0.1170	−0.0973	−0.0499	−0.0578
	Ningxia	Urban	0.1300	−0.0346	0.0046	0.0050	0.0050
	Xinjiang	Urban	0.0697	−0.2201	−0.1650	−0.0428	−0.0546

Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2019.04.003.

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